Data Acquisition and Utilization of Quantum Processed SAR and Optical Images for Scene Classification

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ABSTRACT
Data acquisition, preprocessing, and utilization are the three crucial steps in training deep learning models. The models use vast amounts of data during the training phase. This paper presents the details of the process used for data acquisition from Google Earth Engine, and the images that are preprocessed using quantum computing. A total of 3800 preprocessed images produced, can be utilized to train deep learning models for scene classification. The data is organized into different folders with (i) synthetic aperture radar (SAR) images collected from Sentinel-1 satellite, (ii) optical (OPT) images for the same area as SAR images collected using Sentinel-2 satellite, (iii) processed images using classical processing methods, and (iv) processed images using quantum processing methods. In this paper, we explain in detail the organization of the data and a description of the data. Also, the steps involved in downloading and utilizing the data are explained in detail. We also explain the possible applications of the data and contributions that can be made to the data folders to further increase the scope of the application.

INDEX TERMS data acquisition, preprocessing, quantum computing, scene classification.

I. INTRODUCTION

DATA collection is crucial before training a computational model for scene classification. The classical procedure for creating such a dataset involves collecting and then labeling the collected images category-wise into classes. Further, data can be downloaded and utilized for different applications using machine learning and deep learning models. However, the data available to preprocess and utilize for remote sensing applications using deep learning is very limited [1]. For example, image fusion using SAR and optical (OPT) images requires images of the same location and time period. The unavailability of proper quality datasets will lead to poor training of the model, resulting in inaccuracy in scene classification. Therefore, this paper provides the details of a new semi-automated cloud-based approach to generating data using Google Earth Engine (GEE)) [2]. The collected data is preprocessed using different quantum computing techniques and image fusion. The dataset can train machine learning and deep learning models for remote sensing applications, specifically scene classification [3].

The remaining of the paper is organized as follows: Section II presents the details of the steps followed in data acquisition using GEE. The description of the data is given in Section III along with sample images for each category of images. Finally, we conclude the paper in SectionIV with future scope.

II. SAR AND OPT IMAGE DATA

Our work collected satellite images consisting of 100 SAR images and 100 optical images of the same area tile and of the same time period. The SAR images are further categorized into two classes based on the ground truth of the images. The areas of interest for our data collection are urban development and landmass. The images are aimed for utilization in remote sensing applications. The images are collected using the GEE platform. Initially, geographic location coordinates are selected manually to identify the areas of interest. Two resultant image tiles are collected where the first is the SAR image from the Sentinel-1 satellite, and the second is an OPT image of the same location area and at the same time period from the Sentinel-2 satellite. The geographic coordinates of locations were taken based on the ground truth. For example,

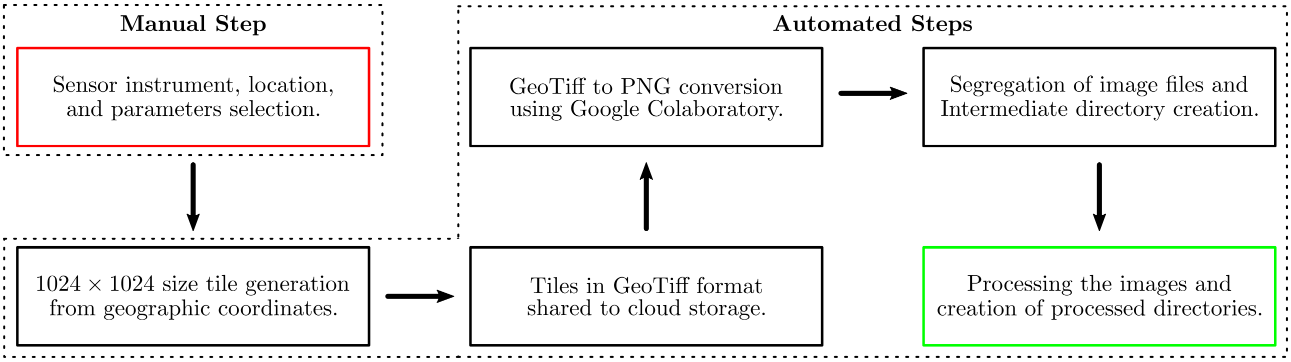


FIGURE 1: Data acquisition from Google Earth Engine.

the location coordinates for the class of urban development, in particular airports, are chosen based on the gross domestic product (GDP) [4] of a particular nation in the year 2020. The approach is followed by the belief that the collection of imagery on such a class-specific basis could help diversify images in a class. The sequence of operations involved and the detailed procedure of data acquisition are depicted in Fig. 1.

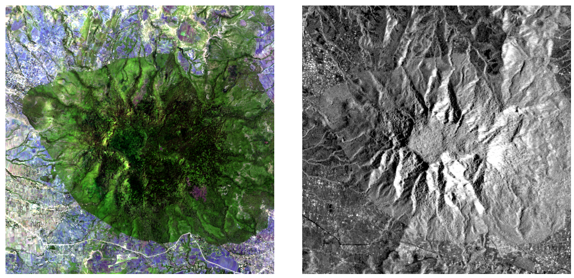
SAR and OPT image tile output size of the same location patch is limited to 1024×1024 as the target objects of interest are covered using that image size. The resulting tiles are downloaded to Google cloud storage in GeoTiff format [5]. GeoTiff images are difficult to process. Hence, the images are converted to portable network graphics (PNG) file format to process using quantum computing. The converted images of each class are then randomly segregated into two subdirectories, namely 'train' and 'val,' in a ratio of $4 : 1$.

III. ORGANIZATION OF THE DATA

Satellite images collected and processed using quantum computing techniques are grouped into five directories. The directory wherein the converted images from GeoTiff format to PNG file format are stored named 'PNG_Input.' The directory with randomly selected images and reorganized into 'train' and 'val' subdirectories are named 'Intermediate.' The remaining three directories contain processed images of the parent SAR and optical image pairs from the 'Intermediate' directory. The first of the remaining three directories was named 'CM_Outputs' and contained processed images that are a result of classical processing techniques. The following two directories were named 'PM1_Outputs,' and 'PM2_Outputs', containing processed images that are results of two different sets of quantum processing techniques. Details of the contents in the five directories are as follows:

A. PNG_INPUT DIRECTORY

'PNG_Input' directory has two subdirectories, namely 'Optical_Dataset' and 'SAR_Dataset.' Each subdirectory have two classes of dataset denoted as '0' and '1' and each class with 50 image files named from '0.png' to '49.png'. The directory consists of 200 image files equally split into two subdirectories.



(a) (b)

FIGURE 2: Sample images from Intermediate directory.
(a) Optical_Dataset/train/1/0.png.
(b) SAR_Dataset/train/1/0.png.

B. INTERMEDIATE DIRECTORY

'Intermediate' directory also contains two subdirectories, namely 'Optical_Dataset' and 'SAR_Dataset.' Each subdirectory has two folders named 'train' and 'val.' Each of these folders consists of two classes of data denoted as '0' and '1'. Each class in the 'train' folder consists of randomly chosen 40 image files. The corresponding class in the 'val' folder consists of the remaining ten image files. The names of image files can range from '0.png' to '49.png'. Therefore, this directory also has 200 image files equally split into the two subdirectories. Two sample image pair files both named '0.png' with file paths of 'Dataset/Intermediate/Optical_Dataset/train/1/0.png' and 'Dataset/Intermediate/SAR_Dataset/train/1/0.png' are shown in Fig. 2. For easy understanding, the notation of **Tree** is used to denote the exact organization of folders and files in 'Optical_Dataset' or 'SAR_Dataset' in the 'Intermediate' directory.

C. CM_OUTPUTS DIRECTORY

'CM_Outputs' directory consists of processed images of two different image fusion methods performed using classical processing methods and hence consists of two subdirectories named 'CPT1_Out' and 'CPT2_Out'. The folders

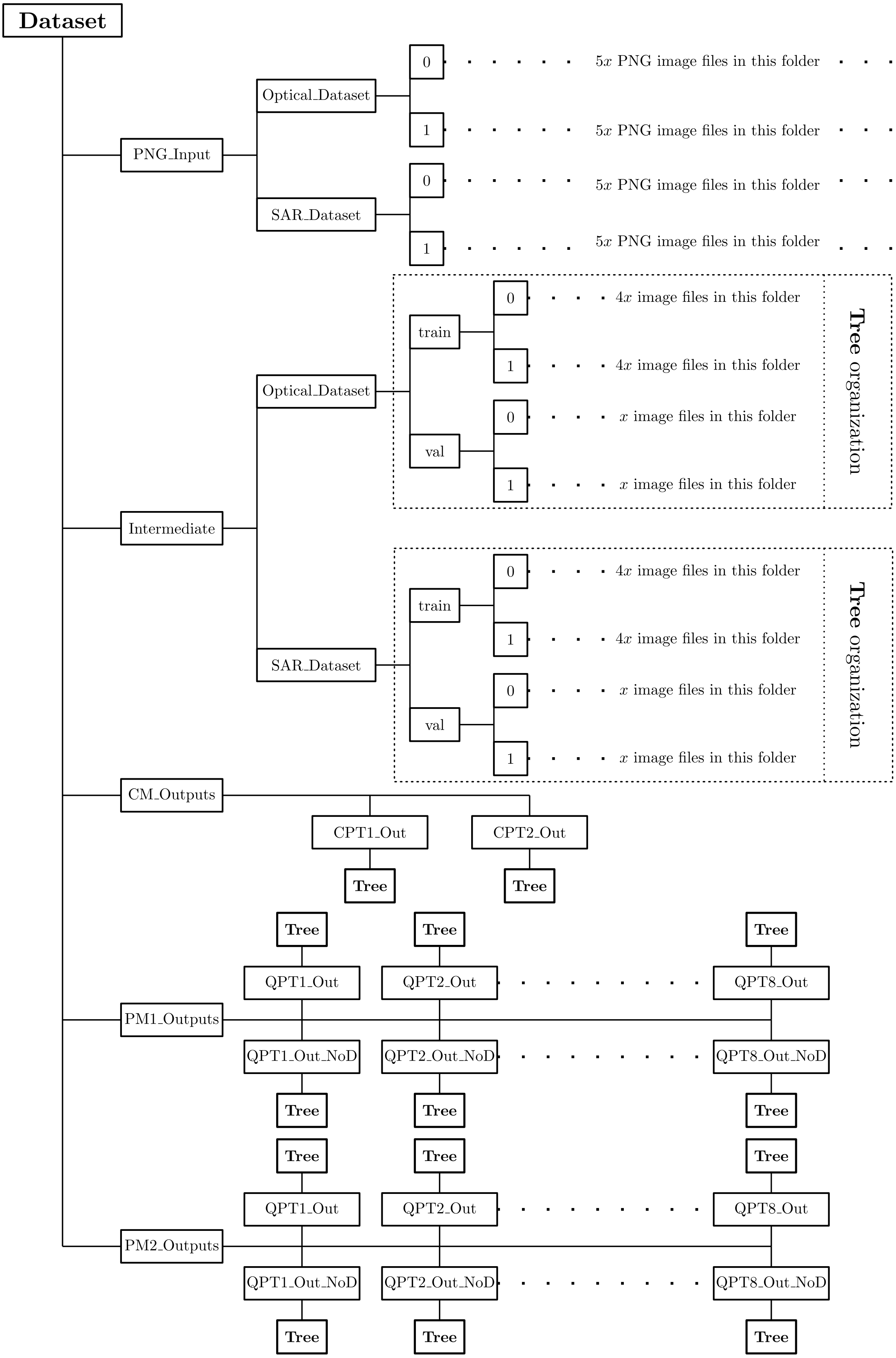
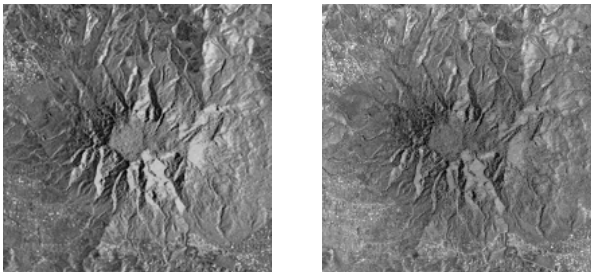
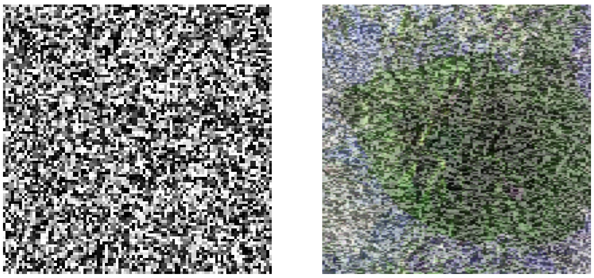


FIGURE 3: Data organization with value of x equals 10.



(a) CPT1_Out/train/1/0.png (b) CPT2_Out/train/1/0.png

FIGURE 4: Sample images from CM_Outputs directory.



(a) QPT1_Out/train/1/0.png (b) QPT8_Out/train/1/0.png

FIGURE 5: Sample images from PM1_Outputs directory.

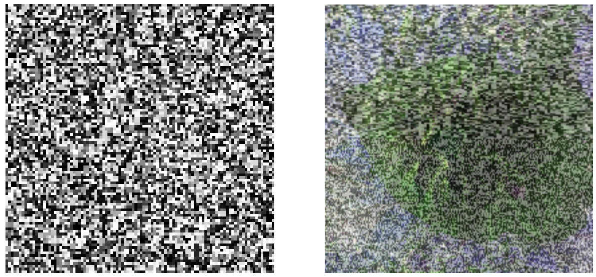
and files within the two subdirectories follow **Tree** organization as shown in Fig. 3. The total number of image files in this directory is equal to 2×100=200. Two sample processed image files both named '0.png' with file paths of 'Dataset/CM_Outputs/CPT1_Out/train/1/0.png' and 'Dataset/CM_Outputs/CPT2_Out/train/1/0.png' are shown in Fig. 4.

D. PM1_OUTPUTS DIRECTORY

'PM1_Outputs' directory consists of processed images using sixteen different image fusion methods performed using quantum processing techniques. Hence, the directory contains sixteen subdirectories from 'QPT1_Out' to 'QPT8_Out' as the first type and from 'QPT1_Out_NoD' to 'QPT8_Out_NoD' as the second type. The folders and files within all these sixteen subdirectories follow **Tree** like organization. The total image files in this directory are equal to 16×100=1600. Two sample processed image files both named '0.png' with file paths of 'Dataset/PM1_Outputs/QPT1_Out/train/1/0.png' and 'Dataset/PM1_Outputs/QPT8_Out/train/1/0.png' is shown in Fig. 5.

E. PM2_OUTPUTS DIRECTORY

'PM2_Outputs' directory organization issame as the previous 'PM1_Outputs' directory, the only difference is that the processed image files are the output of an entirely different set of quantum methods compared to 'PM1_Outputs' directory. The total image files in the directory are equal to 16×100=1600. Two sample pro-



(a) QPT1_Out/train/1/0.png (b) QPT8_Out/train/1/0.png

FIGURE 6: Sample images from PM2_Outputs directory.

cessed image files both named '0.png' with file paths of 'Dataset/PM2_Outputs/QPT1_Out/train/1/0.png' and 'Dataset/PM2_Outputs/QPT8_Out/train/1/0.png' are shown in Fig. 6.

F. DATASET AVAILABILITY

Dataset of our work can be downloaded from Systems and Networks lab website [6] or request for direct download can be made through the drive link [7]. Also, email can be sent to the corresponding author for more details.

IV. CONCLUSION AND FUTURE SCOPE

Deep learning models require vast amounts of data during the training phase for any real-time applications. In our work, we provided a total of 3800 images acquired from GEE and preprocessed using quantum computing techniques. The preprocessed images can be utilized for remote sensing applications such as scene classification and land-use classification. The immediate future scope of our work is that the original SAR and OPT images provided can be processed using different image processing techniques. The processed images can be utilized for many deep learning applications in remote sensing. Also, using the procedure mentioned in our paper, additional images can be collected from multiple geographical locations.

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